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Litter Detection Based on Faster R-CNN

Vishal Yadav[1], Michelle Trivedi[1], Mona[1], Jayshree Chaudhari[1], Fraz Bagwan[1]
[1]Dr. Dy Patil School of Engineering, Savitribai Phule Pune University, Pune, Maharashtra India

ABSTRACT

Cleanliness of city streets has an important impact on city environment and public health. Conventional street cleaning methods involve street sweepers going to many spots and manually confirming if the street needs to clean. However, this method takes a substantial amount of manual operations for detection and assessment of street's cleanliness which leads to a high cost for cities. Using pervasive mobile devices and AI technology, it is now possible to develop smart edge-based service system for monitoring and detecting the cleanliness of streets at scale. This paper explores an important aspect of cities - how to automatically analyse street imagery to understand the level of street litter. A vehicle equipped with smart edge station and cameras is used to collect and process street images in real time. A deep learning model is developed to detect, classify and analysis the diverse types of street litters such as tree branches, leaves, bottles and so on. In addition, two case studies are reported to show its strong potential and effectiveness in smart city systems.

Keywords: Smart City, Street Cleanliness.

I. INTRODUCTION

Urban street surface receives waste deposits from both natural and human sources, such as leaves, soil, sediment, scattered trash, illegal dumpling and so on. When the street cleaning service is ineffective, it could cause a negatively impact on city tourism, reputation, and economy. Furthermore, dirty street have also been recognized as potentially important contributor to air and water pollution. Researches have proved that if there is litter on the streets, people do not hesitate in throwing more litter.

However, if the streets are clean, people tend to think twice before throwing anything and end up not throwing the litter on streets. Therefore, cleanliness of city streets is particularly important as it has a significant effect on city's image and reputation, and on the quality of life for those who live and work in the city.

Currently, many cities have adopted various methods and made great effort to improve the cleanliness of their streets. For instance, New York city used an inspection program called Scorecard to measure the cleanliness of city streets and sidewalks [23]. [20] proposed a cleanliness index for the city of Granada (South of Spain) to measure the level of cleanliness of the streets. In 2015, Imteaj et al. constructed an android based application for the city Dhaka, capital of Bangladesh. The user himself can contribute to clean his city, notify volunteer to come forward or can inform city corporation. In 2015, Los Angeles had developed a state-of-the-art street-by-street [12] cleanliness assessment system. Los Angeles is the first city to map the cleanliness of every one of its blocks. With this new tool, Sanitation is better equipped to target areas of high need, and to ensure a fair allocation of services.

Despite these methods provided new ideas for cities to clean their streets, most of the current methods for detection litter are not fully automated and still rely on human intervention. The clean-up crews need to capture and identify each picture manually to determine if the street is dirty. Therefore, a promising and optimal solution should automatically and reliably detect litter in each captured image without human intervention.

The major motivation of this paper is providing cities with an automated way to monitor the street cleanliness. In this paper, we have studied a smart clean street service application using the state-of-art advanced technologies in IoT, mobile edge computing, big data analysis, as well as machine learning techniques. The mobile edge processing component located in the vehicle which carries the cameras. It shall be able to process the images using a limited computing power and send those images to the service server which may benefit from deeper scan using the powerful GPU processing on the server. After the images pre- processing at the edge layer, Faster R-CNN (Faster Region- Convolutional Neural Network) is used to

identify the street litter at the service server. Finally, the analysis results are sent to user layer for evaluation.

The main contribution of this paper can be summarized as follows. First, we constructed a unique litter data set of 12346 images for training deep-learning based detection models. The second contribution is a litter detector which can detect 11 classes of litter with good accuracy. The third contribution is an edge computing framework of deep learning for smart city street cleanliness.

The rest of the paper is organized as follows. In Section 2, we introduce related work in smart street cleaning, deep learning, and edge computing. In Section 3, we present the architecture, components, and algorithms for the proposed system based on deep learning and edge computing. In Section 4, we describe the implementation details of our system. Section 5 presents the evaluation results. Finally, in Section 6, we make concluding remarks.

II. Motivation

Keep India Beautiful aims to create a cleaner India and hosts community clean up events across the country. However, their events are done without any strong statistical data. With the data which could be taken from our algorithm, they will be able to identify the locations in the India that needs to be cleaned up the most.

Clean India will lead to decrease in the number of deceases caused by unhygienic atmosphere.

The major contributions of this paper are presented as follows.

- We studied a Faster R-CNN open source framework with region proposal network and Resnet network algorithm, using ResNet network to replace the previous VGG network as the basic convolution layers.
- To optimize the performance of the model, we collect urban scene images containing garbage and urban scene images without garbage. By using fine-tuning strategy, we apply the pre-training model parameters which has been trained in coco dataset to our network.
- We propose a dataset fusion strategy, which integrates the garbage dataset with several other

datasets of typical categories in urban scenes. In summary, the method has near- real time and generalization capabilities. Through experiments, we observe that the false detection rate of the garbage area y

III. Related Work

This section reviews the existing research work and related projects.

Smart street cleaning:

The cleanliness of city street is directly related to the city's public image. To maintain the streets clean, different methodologies have been developed in the past years. These methodologies can be classified into two directions: evaluating the street cleanliness, monitoring the waste. In order to evaluate the street cleanliness, Seville etal.proposed a clean index for measuring the level of cleanliness of the city streets, such that the quality and governance of public services can be evaluated. However, the process of measurement requires a lot of human intervention like collecting data and rating data. Lopez et al. develop an App to evaluate the street cleanliness and waste collection service. Specific methods for calculating and evaluating indicators have been designed to give a true reflection of the level of city street cleanliness.

Although this App can collect information from the user end and store information in the application database, it still needs users to fill the information manually in the App. Li et al. put forward a multi-level assessment system and showed how the cleanliness status of streets is collected by using mobile stations. The results are transmitted through city network, analysed in the cloud and presented to city administrators online or on mobile. Regarding monitoring the waste, Rovetta . used sensors to monitor waste bins based on distributed sensor technology and geographical information systems. Begur et al.[3] focused on illegal dumping problems in the City of San Jose. They proposed an innovative smart mobile-based service system, which supports real-time illegal dumping detection, altering, monitoring, and management. Alfarrarjeh et al. [1] presented an automating geo-spatial classification approach to determine the level of street cleanliness. The experiments compared various combinations of classifier and image features, which show that SVM classifier based on CNN image features obtained good values on both precision and recall.

Balchandani et al. [2] proposed a deep learning framework for smart street cleaning, which aims at providing any city with an automated way to monitor the cleanliness of its streets. It is a good idea to use deep leaning technology to automatically detect and classify litter, but this paper only provided with a simple example about separating the street and the curb, and the performance of detection and classification was not discussed. The proposed approach in this paper is also based on recent advances in deep learning.

Related work in deep learning is introduced in the next paragraph.

IV. System Design

This section presents the overall infrastructure of the system. All modules are explained in detail.

System Infrastructure:

Due to the recent advances of IoT technologies, mobile edge computing, big data analysis, as well as machine learning, we designed the system architecture of the proposed smart clean street service system, depicted in Fig. 1. It shows that the system architecture includes three layers: edge layer, cloud layer and user layer. First, images of streets are captured on a mobile device and pre-processed at the edge layer. Also, the end mobile device could record the geological location and provide location awareness for end users. Then, these pre-processed images with location information will be sent from

the edge layer to cloud layer. The cloud-based server performs additional processing on the incoming images and then pushed them through a deep learning algorithm for object detection and classification. Finally, the detail results including litter location, types of litter, and litter detection photos are fed into the end user database for visualization and reporting.

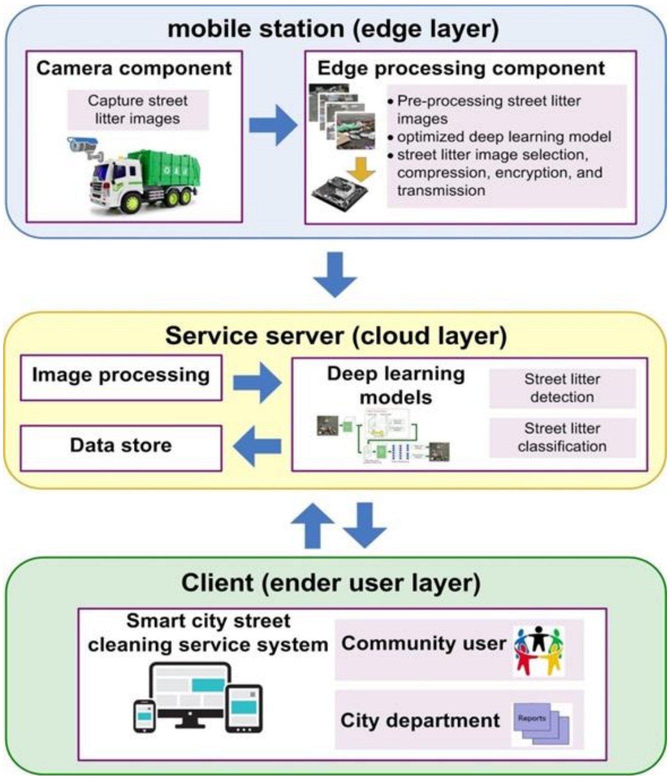

Figure 1: Clean Streets Framework -System Architecture [24]

Edge layer: The main goal of this layer is to capture the street images and collect location coordinates from streets using a smart vehicle with a mobile station. This mobile station has two major components: Camera module and Edge processing module. Three cameras in different direction takes high-resolution pictures of the street. Each camera has a predefined angle and resolution which can be customized and covers defined range 20ft. All these captured pictures are completely in raw or uncompressed, and passed into the edge processing module. The edge processing module is made of several parts. First, an optimized pre-trained deep learning model is used to determine any regions of interest in images which are worth deeper processing in the server, and to check whether the image contains a clear view of the street and is not blur. Then, the selected images are compressed,

encrypted, and finally transmitted to the server through the wireless network.

Server layer: This is the layer where the pre-processed images are further analysed on the cloud server, which is configured to use Tensor flow (an open source software interface) for CNN model training and testing. First, the server-side image processor decrypt the image. Then, the decrypted image is fed into the pre-trained deep learning models like Faster-RCNN which detect and classify the object in the image. Lastly, results generated by the object detection and classification are fed into the end user database for visualization and reporting. User layer: This is the layer where reports are generated based on the Cloud processing. These results including litter location, types of litter, and litter detection photos are visualized for city and community.

Network architectures for litter recognition:

1) Faster R-CNN

In this section, we introduce the key aspects of the Faster R-CNN. [18] Faster R- CNN uses CNN layers named Region Proposal Network (RPN) instead of Selective Search. Faster R-CNN generates region proposals from feature maps generated by RPN. RPN scans the sliding window on the feature map and extracts object candidates.[10] At this time, in order to detect long slender objects, each grid have some bounding boxes called anchor boxes. Finally, like the Fast R- CNN, the region proposals are projected onto the feature map, and the object is detected by classifying region proposals. Since Faster RCNN generates image features and region proposals using single CNN, there is an advantage that end-to-end training can be performed in addition to faster detection

V. CONCLUSION

This paper presents a deep learning based smart street cleaning service system that allows for automatic litter detection and classification and real- time monitoring of the streets conditions. In the proposal system, we studied deep learning model for little street object detection and classification. We have successfully learned and studied python language and have also acquired knowing about libraries like tensorflow and have also learned about object detection and image classification algorithms.

edge-based service system for street cleanliness assessment.

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